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A Classification Method of Coconut Wood Quality Based on Gray Level Co-Occurrence Matrices

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Abstract— **Coconut tree grows rapidly in tropical region such as Indonesia. Coconut wood is used as alternative or complementary raw material for housing or making furniture. Abundant coconut trees are planted, however the utilization of coconut wood as raw material for furniture is still very rare in Indonesia. This is caused by the low quality of coconut wood, since it has not found adequate technology for the processing of coconut wood. This paper presents our experimental work on coconut wood quality classification using self-tuning MLP classifier (AutoMLP) and Support Vector Machine (SVM). For SVM classifier we used the LibSVM library, available in RapidMiner. The Gray-Level Co-occurrence Matrix (GLCM) is used to extract the texture features of coconut wood images. Experiment result shows that AutoMLP gives the best accuracy rate at 78.82%, which is slightly better than 77.06% of SVM.**

Keywords—coconut wood classification; artificial neural network; support vector machine; gray level co-occurrence matrix; texture features

I. Introduction

The quality of coconut wood in the furniture industry requires control to be a ready-made product during the process of material selection to the end of the process. Traditionally, coconut wood grading has been performed by traditional trained human graders [1]. Therefore, objectivity and repeatability are the disadvantages of this traditional system. This course will rely heavily on the expertise and experience of the people who do the inspections.

Automatically grading by not relying on human expertise and experience is the solution for the objectivity and repeatability problem. Recently, there is wide research in wood defect classification. Marcano-Cedeño *et. al.* [2] implement an Artificial Metaplasticity Multi-Layer Perceptron (AMMLP) in order to classify defects in wood images. Classification is based on the features obtained from Gabor filters. Experimental results show that AMMLPs reach better accuracy than the classical Back-Propagation Neural Network (BPNN).

Zhao Dong [3] has studied wood damage recognition by neural network. The results showed that the Artificial Neural Network (ANN) provides an efficient approach to the identification and quantification of the wood damages. Singh *et. al.* [4] proposed Haar wavelet transform and BPNN for texture image classification. There are 15 categories on their dataset collected from Brodatz [5]. They stated that their proposed method is simple and computationally less expensive for texture wood classification.

In this paper, AutoMLP and SVM based on GLCM are used to solve the objectivity and repeatability of coconut wood quality selection. AutoMLP is a simple ANN's model for automatically adjust learning parameters. In our experiment, we use LibSVM library [6], available in RapidMiner. ANN and SVM are the two popular strategies for classification problems. This paper is organized as follows: in the next section brief overview of coconut wood is discussed. In section III, the proposed automatic grading system of coconut wood is described in details. Section IV demonstrated the result of the experiments. In the last section, several conclusions and future work are presented.

II. Brief Overview Of Coconut Wood Quality

The visual grading of coconut wood is determined by the density of bundle pattern on slices of coconut wood. Generally, the coconut wood can be classified according to three degree of density: low density (low quality), medium density (medium quality), and high density (high quality). Fig. 1 shows the various densities of coconut wood quality.

Fig. 1. Coconut wood quality example

III. Research Methodology

ANN and SVM are used to classify automatically wood quality images. This study use texture feature extraction since our classification depends on texture feature of the images. Preprocessing needs to be performed for raw dataset images. Fig. 2 shows the flowchart of wood quality classification. Detailed explanation is described in the following subsection.

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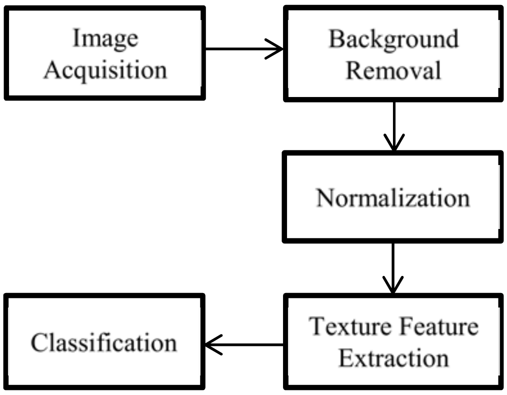


Fig. 2. Grading Process

A. Image Aquisition

In order to evaluate our proposed method, this paper has collected 170 coconut wood texture images from PIKA timber industry education in Semarang, Central Java, Indonesia. Our dataset is divided into three types of wood: low density (class A), medium density (class B), and high density (class C). The dataset has been classified manually by three human graders. The example of dataset is shown in fig. 3.

Class A Class B Class C

Fig. 3. The example of coconut wood in various classes before preprocessing

B. Background Removal

This paper used Euclidean distance to remove the background area since our paper focuses on the woods. First, we need to initialize the foreground color in the Red Green and Blue (RGB) color space. We simply set the background color to zero if the distance label is less than 128 (foreground color). This thresholding carried out manually. The result image can be clearly seen in fig. 4. The result of background removal is shown in fig. 5.

Fig. 4. Thresholding example result

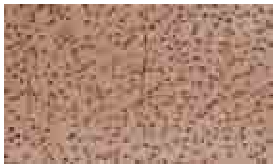
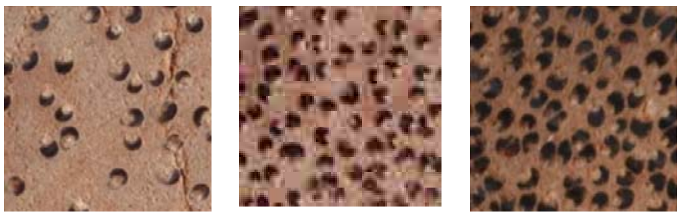


Fig. 5. Background removal example result

C. Normalization of Feature Vector

This paper performed size normalization for the dataset. All images are normalized to size of 256x256. Fig. 6 shows how our experiment selects the area of coconut wood. This selection carried out automatically by choosing in the top left corner of the foreground region. Fig. 7 shows the result of the normalized image of the coconut wood.

Fig. 6. Cropping for size normalization



Class A Class B Class C

Fig. 7. The example of normalized image of the coconut wood

D. Texture Feature Extraction

We used Gray Level Co-occurrence Matrix (GLCM) texture features. GLCM is tabulation of the frequencies or how often different combinations of pixel brightness values (gray levels) occur in an image [7]. From the GLCM, several texture features can be extracted. The computation of the texture features based on the mathematical equations which described in [7] [8] [9] is shown in the following formulae.

$$entropy = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p_{ij} \log p_{ij} \quad (1)$$

$$contrast = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=1}^{N}\sum_{j=1}^{N} p_{ij} \right\}, |i-j| = n \quad (2)$$

$$IDM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{p_{ij}}{1+(i-j)^2} \quad (3)$$

$$correlation = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i-\mu_x)(j-\mu_y)}{\sqrt{\sigma_x \sigma_y}} p_{ij} \quad (4)$$

$$ASM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} {p_{ij}}^2 \quad (5)$$

$$clusshade = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \left(i + j - \mu_x - \mu_y\right)^3 p_{ij} \quad (6)$$

$$cluspro = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \left(i + j - \mu_x - \mu_y\right)^4 p_{ij} \quad (7)$$

$$\max pro = \max_{i,j}\left(p_{ij}\right) \quad (8)$$

$$dissimilarity = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} |i - j|\, p_{ij} \quad (9)$$

$$autocorr = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (ij)\, p_{ij} \quad (10)$$

$$inertia = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i - j)^2 p_{ij} \quad (11)$$

$$dent = \sum_{i=0}^{N-1} p_{x+y}(i)\log\left(p_{x+y}(i)\right) \quad (12)$$

$$sent = \sum_{i=0}^{2N-2} p_{x+y}(i)\log\left(p_{x+y}(i)\right) \quad (13)$$

$$savg = \sum_{i=0}^{2N-2} i p_{x+y}(i) \quad (14)$$

$$s\,\mathrm{var} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i - \mu)^2 p_{ij} \quad (15)$$

$$INV = \sum_{i=0}^{N-1} \frac{p_{ij}}{1 + (i - j)} \quad (16)$$

$$IDN = \sum_{i=0}^{N-1} \frac{p_{ij}}{1 + |i - j|^2 / N^2} \quad (17)$$

$$IDMN = \sum_{i=0}^{N-1} \frac{p_{ij}}{1 + (i - j)^2 / N^2} \quad (18)$$

$$\inf 1 = \frac{HXY - HXY1}{\max(HX, HY)} \quad (19)$$

$$\inf 2 = (1 - \exp[-2.0(HXY2 - HXY)]^{1/2} \quad (20)$$

$$d\,\mathrm{var} = \mathrm{var}\,ianceOf(p_{x-y}) \quad (21)$$

Where p_{ij} is the pixel value in position (i, j) in the output image and N is the number of gray levels in the output image.

E. Classification

AutoMLP and SVM were carried out to classify the quality of coconut wood. Both algorithms are popular strategy for supervised machine learning. AutoMLP [10] is one of the model of ANN that combines ideas from genetic algorithms and stochastic optimization. The idea is automatically adjust learning parameters, as the selection of parameter values to achieve maximal accuracy for the classifier constitutes a difficult problem [11]. Meanwhile, LibSVM is chosen as the SVM tool that supports multiclass classification. LibSVM uses the one-against-one technique to predict the quality of coconut wood. This paper uses *k*-fold cross-validation estimator of generalization performance. Therefore, a classifier uses the same data sample in the training and testing phase. We use 10-fold cross-validation to train and test classifiers which runs the experiment 10 times and averaging the results. The dataset is divided into 10 equally-sized parts. The separated 9 parts as the training set and the remaining part as the testing set.

IV. Experiment And Result

A. Performance Measure

To assess the performance of our proposed model, we used confusion matrix. This measurement is often used for classification evaluation model. By using confusion matrix, accuracy of the classifier can be calculated by using equation (22). There are four conditions in confusion matrix. True Positive (TP) is a positive instance that is classified correctly as positive, if the predicted is wrong it is counted as False Negative (FN). True Negative (TN) is a negative instance that is classified correctly as negative, if the predicted is wrong it is counted as False Positive (FN). Table I shows the confusion matrix for a two class classifier.

TABLE I. CONFUSION MATRIX

Predicted	Observed	
	Actual Positive	Actual Negative
Positive	True Positive TP	False Positive FP
Negative	False Negative FN	True Negative TN

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (22)$$

B. Experiment Result

This paper uses MATLAB[1] and RapidMiner[2] data mining tool to conduct the experiment. All the preprocessing and texture extraction process were conducted in MATLAB and grading system is conducted by RapidMiner. The results of the automatic grading performed by AutoMLP and SVM are shown in table II and table III respectively, which compares the

[1] http://www.mathworks.com/products/matlab/description1.html
[2] http://rapidminer.com/products/rapidminer-studio/

accuracy of classifier in various graders and GLCM parameters. We used 21 features described in section III-D in the classification step.

TABLE II. ACCURACY OF AUTOMLP IN VARIOUS DISTANCES AND DIRECTIONS OF GLCM

GLCM Parameter		Grader 1	Grader 2	Grader 3
Direction	Distance			
0°	1	77.06	61.77	66.47
0°	2	76.47	65.88	57.65
0°	3	76.47	64.12	62.35
45°	1	75.29	63.53	68.24
45°	2	75.88	66.47	65.88
45°	3	71.18	61.77	66.47
90°	1	77.06	67.06	64.12
90°	2	73.53	67.06	68.24
90°	3	**78.82**	67.06	68.82
135°	1	77.06	64.12	60
135°	2	75.88	67.06	63.53
135°	3	77.65	65.88	60.59

We use the various distances and directions for the parameter of GLCM. Three professional graders have been selected to manually grading the coconut wood quality. The performance of AutoMLP classifier represents the best result with accuracy 78.82%, which is slightly better than 77.06% of SVM. Table IV shows the confusion matrix of AutoMLP approach for grader 1 at distance 3 and direction 90° which has the highest accuracy.

TABLE III. ACCURACY OF SVM IN VARIOUS DISTANCES AND DIRECTIONS OF GLCM

GLCM Parameter		Grader 1	Grader 2	Grader 3
Direction	Distance			
0°	1	75.88	60.00	67.65
0°	2	76.47	58.82	66.47
0°	3	76.47	59.41	66.47
45°	1	74.71	59.41	67.65
45°	2	74.71	61.18	64.71
45°	3	76.47	59.41	65.29
90°	1	75.88	59.41	67.06
90°	2	75.29	60.00	65.88
90°	3	75.29	60.00	66.47
135°	1	76.47	59.41	67.06
135°	2	76.47	61.18	66.47
135°	3	**77.06**	60.00	66.47

TABLE IV. CONFUSION MATRIX OF AUTOMLP APPROACH FOR GRADER 1 AT DISTANCE 3 AND DIRECTION 45° OF GLCM PARAMETER

Predicted	Observed			
	Class A	Class B	Class C	Precision
Class A	58	12	0	82.86%
Class B	9	36	7	69.23%
Class C	0	8	40	83.33%
Recall	86.57%	64.29%	85.11%	

V. CONCLUSION

In this paper, AutoMLP and SVM were applied to the coconut wood quality automatic grading. Texture feature extraction using GLCM was used to differentiate among coconut wood images. Experiment result shows that AutoMLP gives the best performance compared to SVM. AutoMLP can be applied automatically to classify the quality of coconut wood with an accuracy rate of 78.82%. For further improvement, feature selection strategy needs to be added to wood quality automatically grading. We can select the worst feature that decreases the accuracy. Feature selection strategy also can be used to speed up the computational time of classifier.

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